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Environmental benefits of bike sharing: A big data-based analysis

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HIGHLIGHTS

- This study quantitatively estimated the environmental benefits of bike sharing.
- Big data techniques were applied to analyse the impacts from a spatiotemporal perspective.
- Bike sharing in Shanghai saved 8,358 tonnes of petrol and decreased CO_2 emissions by 25,240 tonnes in 2016.

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ABSTRACT

Bike sharing is a new form of transport and is becoming increasingly popular in cities around the world. This study aims to quantitatively estimate the environmental benefits of bike sharing. Using big data techniques, we estimate the impacts of bike sharing on energy use and carbon dioxide (CO_2) and nitrogen oxide (NO_X) emissions in Shanghai from a spatiotemporal perspective. In 2016, bike sharing in Shanghai saved 8358 tonnes of petrol and decreased CO_2 and NO_X emissions by 25,240 and 64 tonnes, respectively. From a spatial perspective, environmental benefits are much higher in more developed districts in Shanghai where population density is usually higher. From a temporal perspective, there are obvious morning and evening peaks of the environmental benefits of bike sharing, and evening peaks are higher than morning peaks. Bike sharing has great potential to reduce energy consumption and emissions based on its rapid development.

1. Introduction

Although bike sharing is a relatively new form of transport in urban areas, it has become increasingly popular in towns and cities around the world in recent years [1]. Bike sharing is an oriented production service system (PSS) where ownership of the bike is retained by the provider, who sells the functions of the bike, via modified distribution and payment systems [2–4]. This popularity can be mainly explained by the fact that bike-sharing programmes are associated with various social, environmental, and economic benefits, such as a decrease in carbon dioxide (CO_2) emissions, a reduction in various diseases (e.g., diabetes and obesity), and a decline in traffic congestion and noise pollution through the provision of alternatives to auto-commuting and an increase in public transit use [5–7].

The existing bike-sharing literature can be mainly grouped into two domains [8]. The first domain includes mathematical models that focus on rebalancing. For example, taking London's Barclays Cycle Hire programme as a study case, Pfrommer et al. [9] considered the efficient operation of shared mobility systems via the combination of intelligent routing decisions for staff-based vehicle redistribution and real-time price incentives for customers. Forma et al. [10] proposed a 3-step mathematical programming-based heuristic method for the static repositioning problem. In addition, Pal and Zhang [11] presented a novel mixed integer linear programme for solving real-life large-scale static rebalancing problems. The studies in the second domain include those that characterise bike sharing through various analyses. For example, Wood et al. [12] visualised the dynamics of London's bike-sharing scheme using flow maps, and Zaltz Austwick et al. [13] employed visualisation, descriptive statistics and spatial and network analysis tools to explore usage in five cities around the world. Beecham et al. [14] proposed a new technique for classifying commuting behaviours that involves various spatial analysis algorithms and visual analytics techniques. In addition, Caulfield et al. [5] examined usage patterns of a bike-sharing programme in Cork, a medium-sized city in Ireland. This research provides insights into the dynamics of a relatively small bike-sharing scheme and presents results on how bike sharing has offered citizens a new transport alternative. Some researchers have a particular interest in understanding the factors that affect bike sharing (such as

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the built environment, weather, and socio-economic demographics) [15–17]. Most of the existing studies focus on the analysis of an individual city, such as London (the UK) [9,12,18], Washington DC (the United States) [19,20], Toronto and Montreal (Canada) [21,22], and Hangzhou and Zhongshan (China) [23–25]. However, some studies have performed a comparative analysis of the bike-sharing systems in different cities. These comparisons are based on numerous aspects, such as the number of subscribers/stations/bikes, modal share changes, connectivity, and flows [1,13,26].

However, despite acknowledgement that bike sharing results in various environmental benefits, no studies have directly estimated the environmental benefits of bike sharing. A key contribution of this paper, therefore, is to fill this research gap using a big data technique to quantitatively estimate the impacts of bike sharing on energy savings and emission reductions.

Since the introduction of the first bike-sharing programme in the 1960s, bike-sharing service has evolved quickly over a half century [16,27,28]. We are now facing a new generation of bike sharing, referred to as the dockless (or station-less) bike-sharing service, which is currently emerging in China and expanding around the world. Before the existence of the dockless bike-sharing service, bikes needed to be docked at stations, whereas in this emerging service, bikes can be unlocked and paid for using a smartphone and can be picked up and left any authorised parking area at users' convenience. The first such service was launched in June 2015 by the start-up company ofo. According to the Research Report on Bike-sharing Employment [29], released in September 2017 by China's National Information Centre, the company now has approximately 8 million yellow-framed bikes in more than 170 cities in 9 countries. It has approximately 25 million orders per day and now has 3 billion cumulative orders. The Research Report also shows that at present, there are approximately 16 million dockless bikes in China and 50 million orders per day. In addition, the rapid development of this dockless bike-sharing service has created 100,000 new jobs in China. In particular, 70,000 new jobs were created in the first half of 2017. Because this bike-sharing service is very new, we could only find one existing study: Bao et al. [30] proposed a data-driven approach to develop bike lane construction plans based on bike trip data, provided by Mobike, ofo's main competitor and the world's largest dockless bike-sharing company.

In this paper, we quantitatively evaluate environmental benefits of bike sharing using a large-scale bike-sharing dataset provided by the company Mobike. We estimate the impacts of bike sharing on energy use and CO_2 and NO_X emissions in Shanghai in 2016. Using a big data technique, we discuss the environmental benefits from a spatiotemporal perspective.

2. Data and methods

2.1. Study area and data

With an area of 6341 km^2 and a population of 24.26 million, Shanghai is one of the largest cities in the world and China's economic centre (Fig. 1a). Shanghai's GDP in 2016 was 2.8 trillion Yuan, accounting for 3.6% of China's total GDP [31]. Huangpu, Putuo, Hongkou, Jingan, Changning, Yangpu, and Xuhui districts are regarded as old central area among Shanghai's sixteen districts. Lujiazui, Shanghai's CBD (central business district), is located in Pudong New District and adjacent to old central area. Shanghai's Circle Road is a high-speed road surrounding the most part of Shanghai City (excluding Chongming district). As of July 2017, Shanghai had 1.5 million dockless bikes, making it the largest bike-sharing market in the world [32].

The data used here were obtained from Mobike, which provides 'a bike-sharing service to fulfil urban short trips - anytime, to any authorised parking destination - by combining innovation and today's IoT (Internet of Things) technology' [33]. As of March 2017, Mobike had more than 4 million red-framed bikes in nearly 80 cities worldwide. The company receives approximately 20 million orders per day, accounting for 56.56% of the total market, making it the largest dockless bike-sharing company in the world [34]. The dataset, provided by Mobike, contains approximately 56.62% of total trip orders in August 2016. In it, there were 1,023,603 orders made by 306,936 users for 17,688 bikes. Each order contains the basic trip information, namely, the order identification (ID), user ID, bike ID, start time, the longitude and latitude of the origin, end time, the longitude and latitude of the destination, and *track*. Each attribute is a column in the dataset. The attribute *track* contains the longitudes and latitudes of locations between the start and end locations. For an N-location track, the format of the column *track* is 'longitude1, latitude1# longitude2, latitude2#……. longitudeN, latitudeN#'. It should be noted that all bikes are GPS tracked. Therefore, a bike trip can be regarded as a collection of chronologically ordered GPS points, for example, $p1 \rightarrow p2 \rightarrow \cdots \rightarrow pn$, where each point consists of a geospatial coordinate set and a time stamp such as $p = (x, y, t)$ [35,36]. However, due to privacy issues, the tracks in the dataset were preprocessed by Mobike. Each track contains only a collection of chronologically unordered spatial locations with no temporal information, which means we do not know users' real trip routes. In Section 2.2, we propose a method to solve this issue.

The spatial distribution of the origins and destinations of all bike trips (shown in Fig. 1b) was created using the point density method in ArcGIS, which is developed by ESRI (Environmental Systems Research Institute) and is the world's most widely used commercial GIS (Geographic Information System) software. Most trips occurred in Shanghai's old central area, especially in Yangpu, Hongkou, Jingan, and Huangpu districts. Almost all bikes were used inside Shanghai's Circle Road.

2.2. Trip distance estimation

To estimate environmental benefits, we first need to estimate the distances of the bike trips. The bike-sharing data from traditional dock-based services only contain the longitudes and latitudes of the origin and destination stations. Consequently, the trips have to be represented as a straight line between the origins and destinations, and the trip distances are calculated using a Euclidean distance between the origins and destinations. Considering the bike-sharing data used here also contain the spatial information of the origin and destination locations, we can also calculate the trip distance using a Euclidean distance between the origin and destination. However, this calculation method will underestimate the trip distance. To estimate travel distance more accurately, we propose a method to estimate the trip distances by utilising the *track* information in our dataset.

Assume a chronologically unordered trip T_u can be represented using a collection of chronologically unordered n locations $\{l_1,l_2,...,l_n\}$. l_1 and l_n are the trip's origin and destination, respectively. l_i $(1 < i < n)$ is the spatial location between l_1 and l_n for trip T_u. The following method is used to retrieve chronologically ordered trip T_O from trip T_u. T_O is initially set as {}.

1 Append l_1 to T_O, remove l_1 from T_u, and set $l = l_1$;
2 Find l's closest location l_c from T_u;
3 Append l_c to T_O and remove l_c from T_u;
4 If $l_c = l_n$, T_O is the final chronologically ordered trip; however, if $l_c \neq l_n$, set $l = l_c$, and repeat Steps 2–4.
After retrieving the chronologically ordered trip, we can easily calculate its distance by summing all the distances between the various locations.

2.3. Estimation of vehicle fuels and emissions

We assess the overall energy consumption and environmental impacts associated with all stages of fuels [37,38]. The cycle of vehicle fuels can be divided into two stages: well-to-tank and tank-to-wheels. In